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Article (Accepted Version)

Otten, Marte, Seth, Anil K and Pinto, Yair (2017) A social Bayesian brain: how social knowledge can shape visual perception. *Brain and Cognition*, 112. pp. 69-77. ISSN 0278-2626

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A social Bayesian brain: how social knowledge can shape visual perception

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## Abstract

A growing body of research suggests that social contextual factors such as desires and goals, affective states and stereotypes can shape early perceptual processes. We suggest that a generative Bayesian approach towards perception provides a powerful theoretical framework to accommodate how such high-level social factors can influence low-level perceptual processes in their earliest stages. We review experimental findings that show how social factors shape the perception and evaluation of people, behavior, and socially relevant objects or information. Subsequently, we summarize the generative view of perception within the 'Bayesian brain', and show how such a framework can account for the pervasive effects of top-down social knowledge on social cognition. Finally, we sketch the theoretical and experimental implications of social predictive perception, indicating new directions for research on the effects and neurocognitive underpinnings of social cognition.

Humans are intensely social animals: social interaction in all shapes and sizes forms a core aspect of our existence. The things we know, both consciously (explicitly) and unconsciously (implicitly), about other people helps us to swiftly interpret their behaviour and respond appropriately. In recent years, evidence has mounted that social knowledge shapes not just how we interpret the world around us, but also how we perceive it (see for example Barrett & Bar, 2009). Research from experimental social psychology focussing mainly on visual perception suggests that social contextual factors can subtly but substantially change how a stimulus is processed, which in turn changes the percept that people experience. In this paper, we provide an overview of the experimental evidence that social contextual factors such as goals, desires, emotions, social interpersonal knowledge and stereotypes can significantly influence even the earliest stages of perception. Even though social psychologists have made great strides in uncovering these early perceptual influences of social context, within social psychology there has been a lack of theoretical frameworks in which these findings can be organised. Standard models of human perception emphasize a bottom-up elaboration of sensory information, which imply that higher-level factors such as social context only have a role in later stages, after the corresponding perceptual content has been established. Here, we explore how “predictive perception”, based on the view of the human brain as a pro-active Bayesian hypothesis tester, provides a powerful theoretical framework in which to assimilate the body of experimental findings from social psychology that is now emerging. A key feature of this framework is its emphasis on bidirectional influences between incoming sensory data and prior expectations about the causes of this data (Clark, 2013; Friston, 2010a; Hohwy, 2013; Seth, 2013). This allows researchers studying social cognition to frame questions about whether social context directly affects perceptual content, or whether it (merely) alters post-perceptual processes. In this way, this

framework provides a strong basis from which to derive new, testable hypotheses that stand to substantially enrich the field of social psychological research.

### *1. Social perception*

The idea that high-level social factors such as attitudes, goals and stereotypes can change low level perceptual processes is not new. In the mid-20<sup>th</sup> century the “New Look” movement made the case that social processes critically change basic cognitive functioning (Bruner, 1992). For example, Bruner and Goodman (Bruner & Goodman, 1947) showed that children from poor homes overestimated the size of coins compared to wealthy children. Unfortunately, in subsequent years, many of the New Look experiments were found to suffer from methodological problems (Eriksen, 1962; McCurdy, 1956). Moreover, the design of the experiments makes it difficult to separate true changes in perception (i.e. what a participant sees) from changes in response (i.e. what a participant says). For example, the Bruner and Goodman result could be completely attributed to post-perceptual changes in how a poor child responds to coins, but not how the child perceives the coins, a so-called response bias (Erdelyi, 1974). In the last two decades researchers have shown a renewed appreciation for the ideas of the New Look scientists, which has been accompanied by an increasing body of methodologically rigorous empirical research. Here, we will review this body of research, and explore whether it provides evidence for true changes in perception as a function of social context. To study perceptual processes, researchers can employ several methods. Although asking people to report their (visual, auditory) experience can provide insights into perception, this method is also susceptible to the response biases we described earlier. Another self-report method that seems less susceptible to response biases uses binocular rivalry. In binocular rivalry, different stimuli are presented to the right and

the left eye at the same time. Participants are generally only aware of one stimulus at a time, which means that the two stimuli compete for conscious access. The process of rivalry is thought to primarily reflect perceptual processes, where dominance is the result of competition at early stages of visual processing (Blake, 2001; Tong, Meng, & Blake, 2006). As such, reported changes in conscious perception in a binocular rivalry task are more likely to reflect actual changes in visual perception, rather than response bias (though see Alais, Keetels, & Freeman, 2014). However, binocular rivalry can also be modified by shifts in attention (Meng & Tong, 2004): if participants focus their attention on specific stimuli, these stimuli are slightly more likely to enter awareness than unattended stimuli. Therefore, though suggestive, binocular rivalry studies do not provide definitive evidence that top-down social knowledge *directly* shapes visual processing, since these effects can be (but not necessarily always are) influenced by attention. Electrophysiological studies can be used to unambiguously uncover direct effects of social context on perceptual contents, by examining whether early neural signatures of perceptual processing are modulated by high-level social knowledge. Combined, self-report, binocular rivalry (and other bistable perceptual situations), and electrophysiological data can provide insights into whether social context can indeed change perceptual processes.

Folk psychology often stresses that people see what they want or expect to see. This notion is increasingly supported by studies exploring the effects of expectations, desires and goals on perception. For example, Balcetis & Dunning (2006) presented participants with an ambiguous stimulus, such as a picture that can be seen both as a letter ('B') or a digit ('13'). Before they viewed the ambiguous stimuli, participants were trained to associate digits or letters with a positive outcome in the form of pleasant food. On viewing the ambiguous

stimulus, participants overwhelmingly reported seeing the type of stimulus that was associated with the positive outcome. Balcetis and colleagues (Balcetis, Dunning, & Granot, 2012) linked letters to a financial reward, and numbers to financial loss. In a subsequent binocular rivalry task, letters more frequently achieved initial perceptual dominance, suggesting that the positive outcome associated with one stimulus category changed the visual processing of exemplars from that category. Another binocular rivalry experiment that relied not on learned associations but on the strong intrinsic physiological goal of hunger (Radel & Clement-Guillotin, 2012) showed that hungry participants showed preferences in bistable perception towards items related to food than non-food. Finally, to test the effects of prior expectations on conscious access, Pinto and colleagues (Pinto, van Gaal, de Lange, Lamme, & Seth, 2015) employed a modified binocular rivalry task, a so-called 'breakthrough against continuous flash suppression' paradigm. In this paradigm, one eye views constantly changing Mondrian-style images (which initially dominate conscious perception), while the other eye views an image of an object. Pinto and colleagues (2015) found that expected objects broke through the continuous flash suppression faster than unexpected, or neutral objects (see also Chang, Kanai, & Seth, 2015; Lupyan & Ward, 2013). Together, findings from these studies suggest that participants were not just biased towards reporting the preferred stimuli, but actually were more likely to perceive the stimuli that they wanted or expected to see. This shows that an individual's goals, desires and expectations can influence visual perception and conscious awareness.

Several studies suggest that the affective state of the observer can influence perception. For example, people who are in a positive mood, induced by happy music, are better at detecting mood-congruent than mood-incongruent faces which are obscured by visual noise

(Jolij & Meurs, 2011). In a binocular rivalry study in which one eye was presented with an emotional face and the other with a house, scowling faces were more likely to dominate consciousness compared to smiling faces when the participant was in a negative affective state, and vice versa for participants in a positive mood (Anderson, Siegel, & Barrett, 2011). Singer and colleagues (Singer, Eapen, Grillon, Ungerleider, & Hendler, 2012) showed, in a binocular rivalry experiment, that patients with social anxiety or panic disorders were more likely to see fearful faces (a threat-related stimulus) when the face competed with a house for conscious access, as compared to healthy controls. Changes in the perception of emotionally relevant stimuli also occur when a participant's emotional state is signalled indirectly, through (false) cardiac feedback: When participants are led to believe that their heartrate has increased, a sign of physical arousal, they perceive faces with a neutral expression as more emotionally intense (Gray, Harrison, Wiens, & Critchley, 2007). Taken together, these studies show that the interoceptive or emotional state of the observer can alter what she reports perceiving. Importantly, those studies using binocular rivalry (Gray et al., 2012; Singer et al., 2012) provide additional evidence suggesting that these changes are perceptual. Notably, influences of affective state on perception are not limited to vision. For example, after a fearful mood induction participants perceive sounds as louder than after a neutral mood induction (Siegel & Stefanucci, 2011).

Social influences on visual perception are not just based on the goals, desires and overall emotional state of the observer. Specific social knowledge related to a particular stimulus or person can also directly affect perception. One interesting example from language perception focusses on sarcasm (Regel, Coulson, & Gunter, 2010). Statements that convey irony or sarcasm, such as describing a day spent binge-watching Netflix as 'very productive',



are known to evoke increased early syntactic processing (as indicated by the P600, Spotorno, Cheylus, Van Der Henst, & Noveck, 2013). However, when participants know certain individuals to often speak in a sarcastic way, their ironic statements no longer evoke this relative increase in linguistic processing (Regel et al., 2010). In this study, participants were not asked for explicit judgements or responses – reducing the likelihood of response bias. The dependent measure, the event-related potential, directly reflects neural activation in response to stimuli, and the P600 is known to index initial syntactic processing (Kaan, Harris, Gibson, & Holcomb, 2000). Therefore, this finding indicates that a listener takes into account the speaker's personality in the very first steps of linguistic processing.

Visual perception of others also seems to be modulated by what we know – specifically - about those others. Anderson and colleagues (Anderson, Siegel, Bliss-Moreau, & Barrett, 2011) have shown that faces that have been associated with negative information (“Threw a chair at his classmate”) are preferentially perceived in a binocular rivalry setting, over faces that were associated with neutral or positive information. A number of electrophysiological studies of face perception suggest that effects of social knowledge on face perception originate early in the visual processing stream. For example, faces associated with negative actions (for example raping a woman) evoke a reduced N170 compared to faces that had positive connotations (for example saving a child, Galli, Feurra, & Viggiano, 2006). Since the N170 is thought to reflect initial structural visual encoding specifically of faces, this effect suggests that knowledge about individuals stored in memory directly alters early visual processing of their faces. Negative and positive knowledge about a face also influences the Early Posterior Negativity or EPN (Rahman, 2011; Wieser et al., 2014) and the P100 (Rahman & Sommer, 2012), in patterns that resemble the processing of faces with actual negative or

positive emotional expressions. It thus seems that top-down valence information stored in, and retrieved from, memory can have similar effects as bottom-up sensory visual valence information on early electrophysiological processes underlying face perception. Taken together, the studies summarized above strongly suggest that knowing something about another person (that they are violent, sarcastic or happy) directly influences perceptual processing.

Besides individual knowledge of others, group-based knowledge also plays an important role in shaping our judgment and actions towards others. A simple categorization of others as similar to oneself or different (ingroup vs outgroup) can lead to ingroup favouritism and outgroup discrimination (Mullen, Brown, & Smith, 1992; Tajfel, 1982). In addition, stereotypes about, and negative associations with, a person's race or gender can determine whether they will be offered a job (Ziegert & Hanges, 2005), how much they get paid to do that job (Wood, Corcoran, & Courant, 1993), the quality of medical care they receive (Krieger et al., 2010; Williams & Rucker, 2000), the harshness of sentencing (Bowers, Sandys, & Brewer, 2003), or simply how much distance other people will keep when they are waiting at the bus stop (Dotsch & Wigboldus, 2008). There is now ample evidence that stereotypes and (implicit) biases influence not just behavior, but also perceptual processes. Again, the majority of findings are related to visual perception. For example, Levin and Banaji (2006) demonstrate a striking visual illusion in which for two faces with identical luminance characteristics, the face with African American facial features seems darker than the face with European features (to a mixed group of participants). In another example of changes in visual perception, European Americans are faster to detect anger in African American than European faces (Hugenberg & Bodenhausen, 2003). This effect of race on

emotion perception does not just rely on a change in judgement or responses: the neural representation of the emotion is altered by the race of the face (Otten & Banaji, 2012). In this study, participants watched a face with a specific emotional expression for an extended period of time. This leads to adaptation, such that a new angry face that is viewed after adapting to another angry face is judged to be less angry. This effect is thought to arise because the neurons that encode a specific concept (say an angry face) are depleted after extensive stimulation, leading to smaller neural activation for the same concept when it is presented again (Watson & Clifford, 2003). In the Otten and Banaji (2012) study, the emotion-adaptation effects were smaller when faces differed in race than when the faces were of the same race (but not when they differed only in identity). This suggests that the neural representation of emotion differs depending on the race of a face, supporting findings that indicate changes in emotion perception with the race of the face. In another perceptual effect of race, participants are more likely to misperceive a tool as a weapon after being primed with an African American face (see also Eberhardt, Goff, Purdie, & Davies, 2004; Payne, 2001). In a similar vein, participants taking part in a computer game where they have to shoot only those people who carry a gun are more likely to accidentally shoot black computer avatars carrying tools than white avatars (Correll, Park, Judd, & Wittenbrink, 2002), an effect that also holds for avatars with Muslim headgear (Unkelbach, Forgas, & Denson, 2008).

So far we have given an overview of studies that explored the interaction between high level social knowledge and low-level perceptual processes (for an overview of the effects of non-social high-level factors and perception, please see Vetter & Newen, 2014). The studies described here all indicate that perception can be altered by social contextual factors. While

some effects described here could also be attributed to post-perceptual processes such as response-biases (see for example Klauer & Voss, 2008), several studies provide evidence that conscious perception is directly altered by social context. Psychophysical paradigms such as binocular rivalry suggest that high-level social knowledge can influence visual perception via affecting initial sensory processing stages (Anderson et al., 2011; Anderson et al., 2011; Balcetis et al., 2012). A number of psychophysiological studies show that social contextual information can influence processes related to basic visual (Galli et al., 2006; Rahman, 2011; Rahman & Sommer, 2012; Wieser et al., 2014) and linguistic (Regel et al., 2010) perception. Together, these studies clearly suggest that perceptual processing can be directly shaped by top-down social knowledge.

Overall, the literature on social perception shows highly suggestive evidence for changes in perceptual processes based on higher-level social knowledge and context. These findings sit uncomfortably within classical models of perception that assume bottom-up processing of sensory information which is independent of high-level cognitive factors. Below, we will contrast classical ‘bottom-up’ models of perception with a predictive approach to perception that we suggest provides a valuable theoretical background for accommodating social perceptual effects, and for deriving novel hypotheses.

## *2. Predictive perception*

The visual system is serially attuned to sensory processing: hierarchically low levels are preferentially activated by local details, while hierarchically higher level visual areas respond to information that needs to be integrated and combined over larger visual angles (Van Essen, Anderson, & Felleman, 1992; Zeki et al., 1991). This serial architecture has been the

basis for an almost implicit assumption that visual processing is a serial, bottom-up process (Hochstein & Ahissar, 2002; Hubel & Wiesel, 1968; Perrett & Oram, 1993; Riesenhuber & Poggio, 1999; Serre, Oliva, & Poggio, 2007) where processing at successively 'higher' hierarchical levels results in perceptual content which can be interpreted and integrated with other information already present in the cognitive system (see Figure 1a for an illustration). Within such a framework, perception is usually understood as being cognitively impenetrable (Pylyshyn, 1999): high-level cognitive factors such as mental states and contextual knowledge do not and cannot affect the low-level processing of sensory input. Only at a later stage, when the perceptual content has been formed, can high-level cognition exert its influence, changing for example the interpretation of the stimulus, or the way the perceiver responds to it. Such a framework cannot easily account for effects described above, specifically those studies that show psychophysiological or electrophysiological evidence that the perceiver's goals, desires, inter-personal and group-based social knowledge can change even the early stages of (visual) perception.

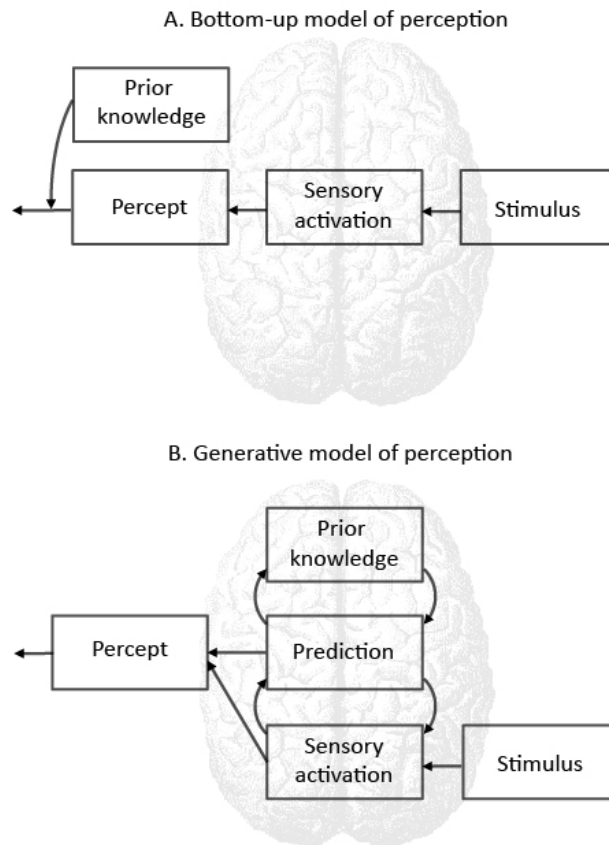


Figure 1: Schematic representation of a stimulus-driven model of perception (panel A), where prior knowledge can only exert an effect after a percept has been formed, and a model of a generative model of perception (panel B) where prior knowledge can influence perception through unconscious inference about the stimulus.

Over the last decade, an old approach to how the brain derives perceptual experience from sensory input has gained renewed emphasis. This approach originates in the writings of Hermann von Helmholtz, the 19<sup>th</sup> century scientist who published a ground-breaking treatise on visual perception *Handbuch der Physiologischen Optik*. In these volumes he introduces the idea that the brain constructs a mental representation of sensory input: through *unbewuster Schluss*, or unconscious inference, by which pre-existing psychological notions present in the mind of the perceiver automatically shape the percept that is generated by the information relayed by the senses (see von Helmholtz, 2005 for a recent reprint of this work).

This idea has inspired the modern concept of perception as predictive processing (Bar, 2007; Bar, 2007; Clark, 2013; Friston, 2009; Friston, 2009; Friston, 2010a; Friston, 2010a; Hohwy,

2013; Kersten, Mamassian, & Yuille, 2004; Knill & Pouget, 2004; Knill & Pouget, 2004), which is emerging as a conceptually compelling and empirically fruitful framework in which to study human perception. In this section, we will first describe the basic process of perceptual inference. The next section will describe the implementation of perceptual processing in a hierarchical architecture such as the brain.

Put simply, predictive processing through perceptual inference assumes perceptual content reflects a representation of the external hidden-causes that are most likely to underlie a specific pattern of sensory activation. For deciphering the most likely set of hidden causes given a particular sensory situation (which is referred to as the *posterior*) two sources of information are combined: the *likelihood* and the *prior*. The likelihood model is the internal representation of sensory input. The prior reflects the initial hypothesis about the likely causes of sensory input, before any input was actually encountered. More simply put, the prior represents internal expectations about the causes of sensory input. Perceptual priors are assumed to depend on previous experiences and knowledge stored in memory, as well as on constraints ‘hard-wired’ through evolution and development. Combining the prior and likelihood estimates through (approximations to) Bayes’ theorem yields an estimate of the posterior, which is assumed to specify perceptual content (see figure 1b for a schematic view of predictive perception).

Figure 2 shows an illustration of how the prior and likelihood are combined to generate a posterior perceptual representation, for a simple example of emotion perception. Arriving at work, imagine that you see a glimpse of a colleague’s face just before they turn back to their computer screen. This quick visual impression provides sensory input. On the Bayesian view, your brain meets this bottom-up (or ‘outside-in’) sensory flow with top-down (or

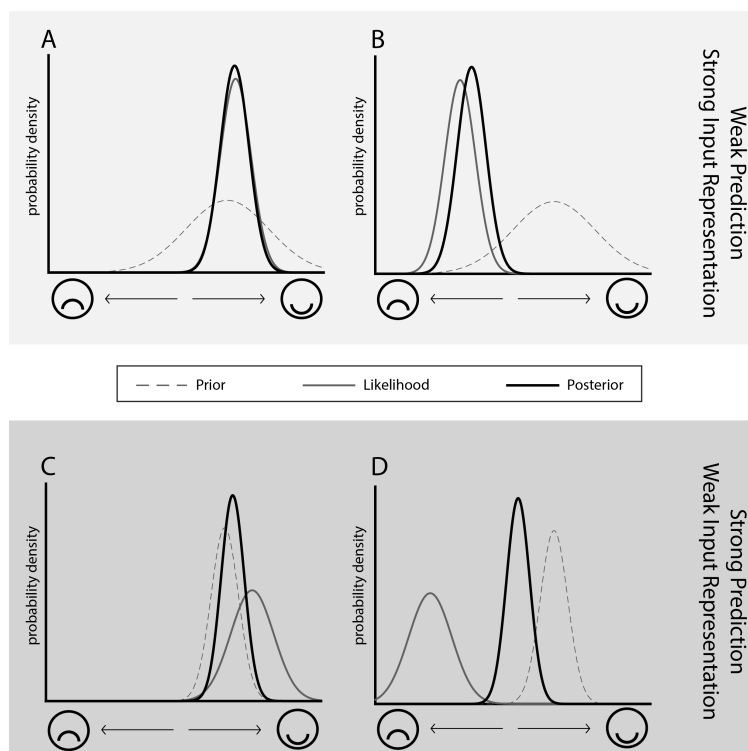
‘inside-out’) expectations, based on context and memory. How sensory data and prior expectation are combined depends critically on the relative precision of these factors. In our example, low precision priors may reflect relatively weak expectations – for example that people are overall slightly more likely to display a happy expression than a sad expression. Precision in sensory data is a function of its reliability – unambiguous sensory data will be afforded high precision, as compared to noisy or otherwise ambiguous data.

Panel 2A show what happens when a low precision internal prior for happiness is combined with high precision sensory evidence for happiness. The resulting posterior for a happy facial expression has high precision, underlying a clear perceptual content signalling a happy face. If this same low precision prior for happiness is combined with high precision evidence for an unhappy facial expression, as illustrated in panel 2B, the posterior now indicates unhappiness due to the strong relative contribution of the high precision likelihood.

In cases 2A and 2B, priors do not play a large role in perceptual inference because they have low precision compared to the sensory evidence. But priors are not always this weak, and perceptual evidence is not always perceived or encoded so clearly. If we consider another colleague whose paper was just accepted in a high impact journal, you may apply a very high precision prior for positive emotional manifestations (as illustrated in 2C and 2D). When these precise priors are combined with relatively weak (low precision) visual input (despite the high impact publication, your colleague still resides in a dark basement office with poor lighting), the priors will have a large influence on the posterior and hence the resulting perceptual content. Figure 2C illustrates how a low-precision sensory input signal can underlie a clear perceptual conclusion when combined with a high precision prior: even



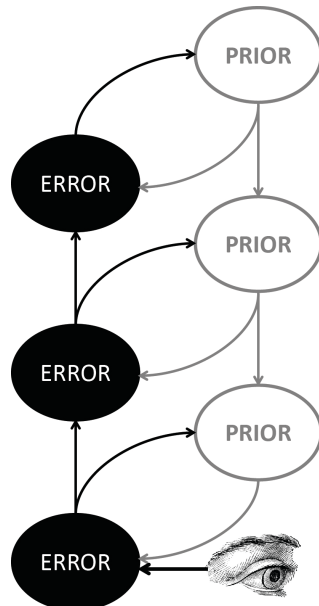
though the badly lit office presents only imprecise visual signals reflecting your colleague's smiling face, the strong resulting perceptual content (the posterior) is boosted to high precision by the strong prior. Finally, example 2D illustrates how strong prior expectations can *change* perception: here, the low precision sensory input signals a negative emotional expression. However, combined with the high precision 'accepted-article induced' prior for happiness, the posterior, and thus the perceptual content, settles on a neutral facial expression. Example 2D indicates that expectations have the potential to shift perceptual content, given the right balance between prior and likelihood.



**Figure 2:** Four examples showing how, following Bayesian computation, different qualities in sensory input (the likelihood) and internal predictions (the prior) influence perceptual outcomes (the posterior). In the top panels the expectations are weak and bottom-up input is precise, so perceived emotion is driven by sensory input. The bottom panels show the reverse situation (weak input, high precision predictions), causing internal expectations to be the main driver of emotion perception.

In examples 2B and 2D, the prior (representing the top-down predictions) and the likelihood function (representing the bottom-up sensory signal) differ from each other. Most versions

of predictive processing propose that such a difference between top-down predictions and bottom-up input gives rise to a prediction *error signal*. Moreover, they assert that perceptual inference is implemented through minimization of these prediction error signals (Bastos et al., 2012; Rao & Ballard, 1999). Inference via prediction error minimization is assumed to take place over multiple levels of perceptual and cognitive processing, so that posteriors at one level form priors for the level immediately below (Friston, 2009; Friston, 2010b; Hohwy, 2012). In a hierarchical scheme, if prediction errors at one level cannot be sufficiently minimized by predictions from the layer immediately above, prediction error will percolate upward through the system (see Fig. 3). This propagation of the error signal to higher levels will lead to updating of successively higher-order (and thus more abstract or conceptual) priors. This in turn gives rise to new sets of perceptual predictions flowing downwards through the hierarchy.



*Figure 3: A hierarchical model of predictive processing. High level neural nodes encode the internally generated expectations about the nature of the input (the prior). These expectations are transmitted down to the lower levels. The difference between the prior and the sensory input is subsequently computed, resulting in an error signal. This error signal is transmitted from the lower level to higher cortical levels, and used to adjust the prior at every level.*

Altogether, the framework of predictive processing shows how high-level cognitive content can play a constitutive role in perception, by participating in the formation of the prior beliefs and likelihood functions that constrain perceptual inference across multiple

hierarchical levels. It is the pre-existing cognitive context, including memories, goals and emotional states and preceding social experience, which forms the basis for the priors. During perception, these priors are integrated with the likelihood of the sensory input to generate the (posterior) percept. As such, the predictive process is doing most of the perceptual ‘heavy lifting’ while the sensory input is providing ongoing feedback or ‘prediction error’ signalling the mismatch between current actual and predicted activity at each hierarchical level (Clark, 2013; Hohwy, 2007).

In recent years, the predictive processing view of perception has been usefully applied to visual perception (Yuille & Kersten, 2006), attention (Chikkerur, Serre, Tan, & Poggio, 2010; Feldman & Friston, 2010; Rao, 2005), interoception (Seth, 2013), action (Adams, Shipp, & Friston, 2013; Shipp, Adams, & Friston, 2013) and decision making (Beck et al., 2008). Of most relevance to the present discussion, the framework has also been applied to highly social aspects of human functioning. For example, the mirror neuron system, an important part of the neural circuitry underlying the ability to understand the actions of others, can be understood as an action-prediction system (Kilner, Friston, & Frith, 2007a; Kilner, Friston, & Frith, 2007b). Brain areas involved in ‘Theory of Mind’, the process of understanding the thoughts, goals and intentions of others, behave in ways that are consistent with predictive processing (Koster-Hale & Saxe, 2013). More generally, it seems that a predictive processing approach is useful to understand how people are able to perceive others’ mental states (Hohwy & Palmer, 2014; Palmer, Seth, & Hohwy, 2015). Human communication also seems to involve predictive processing. Perception of spoken and written words is highly sensitive to contextual cues and top-down knowledge, findings that are difficult to account for within a traditional bottom-up framework of language perception, but which are compatible with a

hierarchical predictive view of language processing (Farmer, Brown, & Tanenhaus, 2013). Moreover, it has been suggested that it is precisely because we are predictive agents that we are able to communicate with other, similarly predictive agents (Friston & Frith, 2015). Along these lines, it has been suggested that too little reliance on priors (for example in autism: Lawson, Rees, & Friston, 2014; Palmer et al., 2015; Pellicano & Burr, 2012; Quattrocki & Friston, 2014; Van de Cruys et al., 2014) hampers effective social functioning. These examples illustrate the explanatory potential that the predictive processing approach has for modelling and explaining social aspects of human cognition.

The distinctive potential of a predictive processing perspective can be highlighted by contrasting it with other frameworks in social cognitive science. For example, *the grounded cognition* perspective postulates that (social) cognition is the result of simulation or re-enactment taking into account stored knowledge from all modalities, which include visual, tactile, sensory, and movement information (Barsalou, 2008; Decety & Grezes, 2006; Goldman, 2006; Meyer & Damasio, 2009). Because cognition directly relies on previous experiences stored in memory, the model leaves ample room for direct top-down effects. However, unlike predictive processing, grounded cognition models assume that internal behavioural simulations only become relevant *after* initial sensory processing has been conducted (Barsalou, 2003; Meyer & Damasio, 2009). This means that grounded cognition does not provide a powerful framework in which to interpret the findings reviewed in section 1, which show that initial sensory processing is influenced by social context. In contrast, a predictive processing approach to perception and cognition provides a neurally plausible description of how simulation processes that are the key component of grounded cognition might be implemented in the brain: not as full scale simulations, but as internally

generated predictions based on knowledge gained from previous (bodily) experiences (Barrett & Simmons, 2015; Seth, 2013).

### *3. Implications for social perception*

As described above, the essence of the predictive processing framework is that prior experience and existing knowledge constrains predictions about the causes of current sensory inputs. By combining priors with the actual sensory input, perceptual content is specified. Within such a framework, desires, goals, emotional states and individual or group-level social knowledge about others all have a potential<sup>1</sup> to contribute to the perceptual predictions that are generated by the system. It is through these predictions that high-level social factors can directly shape perception.

The usefulness of the predictive processing framework for social psychology is not just that it provides a theoretical framework that explains in general terms how high-level social knowledge can influence perception. The framework also provides an impetus to advance the theoretical and experimental work focussing on social cognition. Next, we will outline four experimental hypotheses to illustrate how a predictive processing framework can help develop and answer social psychological questions.

#### *3.1 From active inference to social action*

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<sup>1</sup> Obviously, social states and knowledge can only influence perception if they have predictive value for the perceiver. For example, being angry might make a perceiver more susceptible for violence related cues if that perceiver has often associated anger with violence, while it might make another perceiver more susceptible to food related cues, since that perceiver has associated anger and binge-eating in the past. These differences will prescribe different actions, which in turn will reduce interoceptive predictions errors and promote long-run physiological homeostasis (Seth, 2015)

A central aim for social psychology is to study individual social actions and interpersonal interaction. The predictive processing framework provides an interesting perspective on human action (Friston, Daunizeau, Kilner, & Kiebel, 2010): actions are generated through the fulfilment of internal (proprioceptive) predictions, and can be deployed to minimize sensory prediction errors (e.g., if you expect to see John, move your eyes until John appears). Minimization of prediction error through action is called 'active inference' (Friston et al, 2010). Currently, the active inference model has been applied to basic forms of behaviour, such as oculomotor control (Adams, Perrinet, & Friston, 2012) and simple goal-directed decision-making (Solway & Botvinick, 2012). With regards to social behaviour, the idea of active inference suggests that people are likely to employ actions to confirm their social preconceptions. These actions could be obviously social in nature, such as physically avoiding someone or instigating an interaction with other people, but they could also be not specifically social, such as instigating an eye movement or re-focussing attention. As a concrete example, the active inference framework predicts that people with strong (implicit) gender stereotypes are more likely to search for evidence that confirms their predictions (a woman doing something a mother would do) than for evidence that disconfirms their predictions (a woman doing something a leader would do), or act in ways that will elicit stereotype-consistent behaviour from others. These predictions are in line with experimental observations from Hollingshead and Fraidin (2003), who showed that people in a collective memorization task are more likely to choose gender-consistent memory categories (soap-operas for women, cars for men) over a neutral category (geography) when working with a partner from the opposite gender.

Future research could also examine whether the existence of *competing* social priors leads to (social) actions that best disambiguate these priors, rather than actions which are deployed to confirm a specific prior belief as suggested above. This prediction rests on the notion of *counterfactual* predictive processing, whereby predictive models encode not only the likely causes of current sensory signals, but also the likely causes of sensory signals that are predicted to occur given specific actions (Friston, Adams, Perrinet, & Breakspear, 2012; Seth, 2014). These ideas have only recently been applied in social settings (Palmer et al., 2015), suggesting that counterfactual predictions combined with active inference has strong theoretical potential.

Moreover, future research could test whether social active inference is closely coupled with perceptual effects, i.e., whether those individuals who show strongest modulation of their perception through social stereotypes also show strongest modulation of their behaviour through social stereotypes. Indeed, it may be that people who show strong influence of priors in basic perceptual processes (evidenced, for example, by a strong susceptibility for top-down induced perceptual illusions) may also show a similarly strong influence of priors on social perception.

One important consequence of active inference is *sensory attenuation*: a reduction of attention to the sensory consequences of self-generated behaviour (Brown, Adams, Parees, Edwards, & Friston, 2013). Sensory attenuation can be easily illustrated if you try to tickle yourself: this is much less effective than when someone else tickles you. If social behaviour is indeed a form of active inference, then we may expect to find similar ‘sensory’ attenuation for self-related consequences of social actions. Thus, perhaps our scary story

scares the listeners but not us, because of ‘social sensory attenuation’. And perhaps the hurt we inflict on another person does not allow us to empathize in the way we would be moved by similar, but other-inflicted, pain to that of some person. The empathic response could be reduced through sensory attenuation. However, such a reduction in empathy could also be attributed to a cognitive strategy in which the hurter justifies his/her behaviour by asserting that the consequences are simply not that bad because we are already attuned to the consequences of our own actions. Future research could explore whether our own actions indeed make us less sensitive to the sensory/perceptual consequences of these actions.

### *3.2 Deriving hypotheses about neural patterns of activation*

The predictive processing approach provides a strong insight into how neural populations respond to sensory information that (does not) fit an internal prediction. Compared to unpredicted stimuli, predictable and thus redundant neural activation is suppressed early on in the processing stream (Rao & Ballard, 1999). Therefore, the representation of expected sensory input is sparse, but highly efficient (Jehee, Rothkopf, Beck, & Ballard, 2006). Even though the resulting neural activation for unexpected sensory stimulation appears more widespread (since there is less predicted activation to be suppressed), it will be less efficient at representing the sensory input than the activation for expected stimuli (Kok, Jehee, & de Lange, 2012; Koster-Hale & Saxe, 2013).

If at in a specific area of the brain, expected stimuli give rise to a pattern of activation that is more informative (for example in a MVPA analysis, Kok et al., 2012) than unpredicted stimuli, this suggests that priors influence the representation of the stimulus. If on the other hand expected and unexpected stimuli are equally informative, then the neural



representation seems purely based on bottom-up input, not on top-down predictions. This provides a powerful tool to explore at which neural level social predictions provide strong priors, and at which level they do not. Some social cues might provide low level priors, such as that a violence related cue might activate a dark hue prior when you are anticipating to see a face (Eberhardt et al., 2004). This should thus be reflected in a more efficient pattern of neural activation to expected than unexpected colouring in the earliest colour processing levels of the visual processing system (V3). However, many social priors might only be informative at slightly higher levels of sensory processing. For example in the case of your happy colleague (examples 2C and 2D), it is more likely that predictions about emotional content of the input are represented in the fusiform face area, or the amygdala (Vuilleumier & Pourtois, 2007). By exploring at which level the neural activation patterns are in line with a predictive processing account, and at which level they do not, we can thus not only learn that the brain generates its own hypotheses about the input, but also at which neural levels these hypotheses are used to generate priors about the expected sensory input.

### *3.3 Changing priors through experience*

The predictive processing framework proposes that current priors are continually updated based on feedback from sensory input, in order to optimize future perceptual predictions. Interestingly, current research on social priors suggest that when new information is highly personally relevant, the corresponding priors appear more difficult to shift. For example, when estimating their future chance of divorce or cancer, people tend to discount information that is more negative than their existing estimate (Sharot, Korn, & Dolan, 2011). Beliefs about one's own IQ and appearance are also surprisingly stable, at least when the new information is unflattering for the individual (positive information is integrated into

one's personal beliefs, Eil & Rao, 2011). This suggests a mechanism that maintains stable self-related social priors, even in the presence of (overwhelming) counterevidence.

Future research could explore whether other social priors show similar characteristics, perhaps by systematically ignoring information that is not in line with pre-existing beliefs. For example, people with strong negative associations with African-Americans (Greenwald, Nosek, & Banaji, 2003) might have negative expectations about the behaviour of African-American people in general. Positive behaviour of African American individuals (say, always sharing their money in an iterative prisoner's dilemma), should change the priors of the prejudiced individual to a more positive expectation. If this is not the case, i.e., if the relevant social priors are not updated (or updated to a smaller extent than for non-prejudiced individuals), this shows that prejudice not only affects one's priors but also the how these priors are updated.

Moreover, if phenomena like this are observed, it becomes possible to examine the underlying causes. It may be that social priors have an inherent high precision-weighting, more than non-social priors. It is also possible that active inference (section 3.1) leads individuals to under-sample inconvenient information that does not fit their core world views.

#### *4. Conclusion*

After a hiatus, social psychology has again turned its focus to exploring the interaction between high-level social knowledge and basic perceptual processing. At this point, evidence is mounting that a person's desires and moods, and their knowledge about individuals and groups, can shape perceptual content. Adopting a view of human perception as a predictive process, that relies on internally generated predictions or priors, can not only explain how social knowledge can directly and seamlessly influence perception and consciousness; it also provides exciting new avenues for research and scientific exploration of social perception and social action.

## References

- Adams, R. A., Perrinet, L. U., & Friston, K. (2012). Smooth pursuit and visual occlusion: Active inference and oculomotor control in schizophrenia.
- Adams, R., A., Shipp, S., & Friston, K. (2013). Predictions not commands: Active inference in the motor system. *Brain Structure and Function*, 218(3), 611-643.
- Alais, D., Keetels, M., & Freeman, A. W. (2014). Measuring perception without introspection. *Journal of Vision*, 14(11), 10.1167/14.11.1. doi:10.1167/14.11.1 [doi]
- Anderson, E., Siegel, E. H., Bliss-Moreau, E., & Barrett, L. F. (2011). The visual impact of gossip. *Science*, 332(6036), 1446.
- Anderson, E., Siegel, E. H., & Barrett, L. F. (2011). What you feel influences what you see: The role of affective feelings in resolving binocular rivalry. *Journal of Experimental Social Psychology*, 47(4), 856-860.
- Balcetis, E., & Dunning, D. (2006). See what you want to see: Motivational influences on visual perception. *Journal of Personality and Social Psychology*, 91(4), 612.
- Balcetis, E., Dunning, D., & Granot, Y. (2012). Subjective value determines initial dominance in binocular rivalry. *Journal of Experimental Social Psychology*, 48(1), 122-129.
- Bar, M. (2007). The proactive brain: Using analogies and associations to generate predictions. *Trends in Cognitive Sciences*, 11(7), 280-289.
- Barrett, L. F., & Bar, M. (2009). See it with feeling: Affective predictions during object perception. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1521), 1325-1334.

- Barrett, L. F., & Simmons, W. K. (2015). Interoceptive predictions in the brain. *Nature Reviews Neuroscience*, 16(7), 419-429.
- Barsalou, L. (2003). Situated simulation in the human conceptual system. *Language and Cognitive Processes*, 18(5-6), 513-562.
- Barsalou, L. (2008). Grounded cognition. *Annu.Rev.Psychol.*, 59, 617-645.
- Bastos, A. M., Usrey, W. M., Adams, R. A., Mangun, G. R., Fries, P., & Friston, K. J. (2012). Canonical microcircuits for predictive coding. *Neuron*, 76(4), 695-711.
- Beck, J. M., Ma, W. J., Kiani, R., Hanks, T., Churchland, A. K., Roitman, J., . . . Pouget, A. (2008). Probabilistic population codes for bayesian decision making. *Neuron*, 60(6), 1142-1152.
- Blake, R. (2001). A primer on binocular rivalry, including current controversies. *Brain and Mind*, 2(1), 5-38.
- Bowers, W. J., Sandys, M., & Brewer, T. W. (2003). Crossing racial boundaries: A closer look at the roots of racial bias in capital sentencing when the defendant is black and the victim is white. *DePaul L.Rev.*, 53, 1497.
- Brown, H., Adams, R., A, Parees, I., Edwards, M., & Friston, K. (2013). Active inference, sensory attenuation and illusions. *Cognitive Processing*, 14(4), 411-427.
- Bruner, J. S. (1992). Another look at new look 1. *American Psychologist*, 47(6), 780.
- Bruner, J. S., & Goodman, C. C. (1947). Value and need as organizing factors in perception. *The Journal of Abnormal and Social Psychology*, 42(1), 33.
- Chang, A. Y., Kanai, R., & Seth, A. K. (2015). Cross-modal prediction changes the timing of conscious access during the motion-induced blindness. *Consciousness and Cognition*, 31, 139-147.

- Chikkerur, S., Serre, T., Tan, C., & Poggio, T. (2010). What and where: A bayesian inference theory of attention. *Vision Research*, 50(22), 2233-2247.
- Clark, A. (2013). Whatever next? predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, 36(03), 181-204.
- Correll, J., Park, B., Judd, C. M., & Wittenbrink, B. (2002). The police officer's dilemma: Using ethnicity to disambiguate potentially threatening individuals. *Journal of Personality and Social Psychology*, 83(6), 1314.
- Decety, J., & Grezes, J. (2006). The power of simulation: Imagining one's own and other's behavior. *Brain Research*, 1079(1), 4-14.
- Dotsch, R., & Wigboldus, D. H. J. (2008). Virtual prejudice. *Journal of Experimental Social Psychology*, 44(4), 1194-1198.
- Eberhardt, J. L., Goff, P. A., Purdie, V. J., & Davies, P. G. (2004). Seeing black: Race, crime, and visual processing. *Journal of Personality and Social Psychology*, 87(6), 876.
- Eil, D., & Rao, J. M. (2011). The good news-bad news effect: Asymmetric processing of objective information about yourself. *American Economic Journal: Microeconomics*, 3(2), 114-138.
- Erdelyi, M. H. (1974). A new look at the new look: Perceptual defense and vigilance. *Psychological Review*, 81(1), 1.
- Eriksen, C. W. (1962). Figments, fantasies, and follies: A search for the subconscious mind<sup>1</sup>. *Journal of Personality*, 30(2), 3-26.
- Farmer, T. A., Brown, M., & Tanenhaus, M. K. (2013). Prediction, explanation, and the role of generative models in language processing. *Behavioral and Brain Sciences*, 36(03), 211-212.

- Feldman, H., & Friston, K. (2010). Attention, uncertainty, and free-energy. *Frontiers in Human Neuroscience*, 4, 215. doi:10.3389/fnhum.2010.00215 [doi]
- Friston, K. (2009). The free-energy principle: A rough guide to the brain? *Trends in Cognitive Sciences*, 13(7), 293-301.
- Friston, K. (2010a). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, 11(2), 127-138.
- Friston, K. (2010b). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, 11(2), 127-138.
- Friston, K., Daunizeau, J., Kilner, J., & Kiebel, S. J. (2010). Action and behavior: A free-energy formulation. *Biological Cybernetics*, 102(3), 227-260.
- Friston, K., & Frith, C. (2015). A duet for one. *Consciousness and Cognition*,
- Friston, K., Adams, R. A., Perrinet, L., & Breakspear, M. (2012). Perceptions as hypotheses: Saccades as experiments. *Frontiers in Psychology*, 3, 151. doi:10.3389/fpsyg.2012.00151 [doi]
- Galli, G., Feurra, M., & Viggiano, M. P. (2006). "Did you see him in the newspaper?" electrophysiological correlates of context and valence in face processing. *Brain Research*, 1119(1), 190-202.
- Goldman, A. I. (2006). *Simulating minds: The philosophy, psychology, and neuroscience of mindreading* Oxford University Press.
- Gray, M. A., Beacher, F. D., Minati, L., Nagai, Y., Kemp, A. H., Harrison, N. A., & Critchley, H. D. (2012). Emotional appraisal is influenced by cardiac afferent information. *Emotion*, 12(1), 180.

- Gray, M. A., Harrison, N. A., Wiens, S., & Critchley, H. D. (2007). Modulation of emotional appraisal by false physiological feedback during fMRI. *PloS One*, 2(6), e546.  
doi:10.1371/journal.pone.0000546 [doi]
- Greenwald, A. G., Nosek, B. A., & Banaji, M. R. (2003). Understanding and using the implicit association test: I. an improved scoring algorithm. *Journal of Personality and Social Psychology*, 85(2), 197.
- Hochstein, S., & Ahissar, M. (2002). View from the top: Hierarchies and reverse hierarchies in the visual system. *Neuron*, 36(5), 791-804.
- Hohwy, J. (2007). Functional integration and the mind. *Synthese*, 159(3), 315-328.
- Hohwy, J. (2013). *The predictive mind* Oxford University Press.
- Hohwy, J., & Palmer, C. (2014). Social cognition as causal inference: Implications for common knowledge and autism. *Perspectives on social ontology and social cognition* (pp. 167-189) Springer.
- Hohwy, J. (2012). Attention and conscious perception in the hypothesis testing brain. *Frontiers in Psychology*, 3, 96. doi:10.3389/fpsyg.2012.00096 [doi]
- Hollingshead, A. B., & Fraidin, S. N. (2003). Gender stereotypes and assumptions about expertise in transactive memory. *Journal of Experimental Social Psychology*, 39(4), 355-363.
- Hubel, D. H., & Wiesel, T. N. (1968). Receptive fields and functional architecture of monkey striate cortex. *The Journal of Physiology*, 195(1), 215-243.
- Hugenberg, K., & Bodenhausen, G. V. (2003). Facing prejudice: Implicit prejudice and the perception of facial threat. *Psychological Science*, 14(6), 640-643. doi:psci\_1478 [pii]



- Jehee, J. F., Rothkopf, C., Beck, J. M., & Ballard, D. H. (2006). Learning receptive fields using predictive feedback. *Journal of Physiology-Paris*, 100(1), 125-132.
- Jolij, J., & Meurs, M. (2011). Music alters visual perception. *PloS One*, 6(4), e18861.
- Kaan, E., Harris, A., Gibson, E., & Holcomb, P. (2000). The P600 as an index of syntactic integration difficulty. *Language and Cognitive Processes*, 15(2), 159-201.
- Kersten, D., Mamassian, P., & Yuille, A. (2004). Object perception as bayesian inference. *Annu.Rev.Psychol.*, 55, 271-304.
- Kilner, J., Friston, K., & Frith, C. D. (2007a). Predictive coding: An account of the mirror neuron system. *Cognitive Processing*, 8(3), 159-166.
- Kilner, J., Friston, K., & Frith, C. (2007b). The mirror-neuron system: A bayesian perspective. *Neuroreport*, 18(6), 619-623. doi:10.1097/WNR.0b013e3281139ed0 [doi]
- Klauer, K. C., & Voss, A. (2008). Effects of race on responses and response latencies in the weapon identification task: A test of six models. *Personality and Social Psychology Bulletin*, 34(8), 1124-1140.
- Knill, D. C., & Pouget, A. (2004). The bayesian brain: The role of uncertainty in neural coding and computation. *Trends in Neurosciences*, 27(12), 712-719.
- Kok, P., Jehee, J. F., & de Lange, F. P. (2012). Less is more: Expectation sharpens representations in the primary visual cortex. *Neuron*, 75(2), 265-270.
- Koster-Hale, J., & Saxe, R. (2013). Theory of mind: A neural prediction problem. *Neuron*, 79(5), 836-848.

- Krieger, N., Carney, D., Lancaster, K., Waterman, P. D., Kosheleva, A., & Banaji, M. (2010). Combining explicit and implicit measures of racial discrimination in health research. *Journal Information*, 100(8)
- Lawson, R. P., Rees, G., & Friston, K. J. (2014). An aberrant precision account of autism. *Front Hum Neurosci*, 8, -.
- Levin, D. T., & Banaji, M. R. (2006). Distortions in the perceived lightness of faces: The role of race categories. *Journal of Experimental Psychology: General*, 135(4), 501.
- Lupyan, G., & Ward, E. J. (2013). Language can boost otherwise unseen objects into visual awareness. *Proceedings of the National Academy of Sciences of the United States of America*, 110(35), 14196-14201. doi:10.1073/pnas.1303312110 [doi]
- McCurdy, H. G. (1956). Coin perception studies and the concept of schemata. *Psychological Review*, 63(3), 160.
- Meng, M., & Tong, F. (2004). Can attention selectively bias bistable perception? differences between binocular rivalry and ambiguous figures. *Journal of Vision*, 4(7), 2-2.
- Meyer, K., & Damasio, A. (2009). Convergence and divergence in a neural architecture for recognition and memory. *Trends in Neurosciences*, 32(7), 376-382.
- Mullen, B., Brown, R., & Smith, C. (1992). Ingroup bias as a function of salience, relevance, and status: An integration. *European Journal of Social Psychology*, 22(2), 103-122.
- Otten, M., & Banaji, M. R. (2012). Social categories shape the neural representation of emotion: Evidence from a visual face adaptation task. *Frontiers in Integrative Neuroscience*, 6

- Palmer, C. J., Seth, A. K., & Hohwy, J. (2015). The felt presence of other minds: Predictive processing, counterfactual predictions, and mentalising in autism. *Consciousness and Cognition*,
- Payne, B. K. (2001). Prejudice and perception: The role of automatic and controlled processes in misperceiving a weapon. *Journal of Personality and Social Psychology*, 81(2), 181.
- Pellicano, E., & Burr, D. (2012). When the world becomes 'too real': A bayesian explanation of autistic perception. *Trends in Cognitive Sciences*, 16(10), 504-510.
- Perrett, D. I., & Oram, M. W. (1993). Neurophysiology of shape processing. *Image and Vision Computing*, 11(6), 317-333.
- Pinto, Y., van Gaal, S., de Lange, F. P., Lamme, V. A., & Seth, A. K. (2015). Expectations accelerate entry of visual stimuli into awareness. *Journal of Vision*, 15(8), 13-13.
- Pylyshyn, Z. (1999). Is vision continuous with cognition?: The case for cognitive impenetrability of visual perception. *Behavioral and Brain Sciences*, 22(03), 341-365.
- Quattrocki, E., & Friston, K. (2014). Autism, oxytocin and interoception. *Neuroscience & Biobehavioral Reviews*, 47, 410-430.
- Radel, R., & Clement-Guillotin, C. (2012). Evidence of motivational influences in early visual perception: Hunger modulates conscious access. *Psychological Science*, 23(3), 232-234.  
doi:10.1177/0956797611427920 [doi]
- Rahman, R. A. (2011). Facing good and evil: Early brain signatures of affective biographical knowledge in face recognition. *Emotion*, 11(6), 1397.

- Rahman, R. A., & Sommer, W. (2012). Knowledge scale effects in face recognition: An electrophysiological investigation. *Cognitive, Affective, & Behavioral Neuroscience*, 12(1), 161-174.
- Rao, R. P. N. (2005). Bayesian inference and attentional modulation in the visual cortex. *Neuroreport*, 16(16), 1843-1848.
- Rao, R. P. N., & Ballard, D. H. (1999). Predictive coding in the visual cortex: A functional interpretation of some extra-classical receptive-field effects. *Nature Neuroscience*, 2, 79-87.
- Regel, S., Coulson, S., & Gunter, T. C. (2010). The communicative style of a speaker can affect language comprehension? ERP evidence from the comprehension of irony. *Brain Research*, 1311, 121-135.
- Riesenhuber, M., & Poggio, T. (1999). Hierarchical models of object recognition in cortex. *Nature Neuroscience*, 2(11), 1019-1025.
- Serre, T., Oliva, A., & Poggio, T. (2007). A feedforward architecture accounts for rapid categorization. *Proceedings of the National Academy of Sciences of the United States of America*, 104(15), 6424-6429. doi:0700622104 [pii]
- Seth, A. K. (2014). A predictive processing theory of sensorimotor contingencies: Explaining the puzzle of perceptual presence and its absence in synesthesia. *Cognitive Neuroscience*, 5(2), 97-118.
- Seth, A. K. (2015). Inference to the best prediction. *Open MIND* () Open MIND. Frankfurt am Main: MIND Group.
- Seth, A., K. (2013). Interoceptive inference, emotion, and the embodied self. *Trends in Cognitive Sciences*, 17(11), 565-573.

- Sharot, T., Korn, C. W., & Dolan, R. J. (2011). How unrealistic optimism is maintained in the face of reality. *Nature Neuroscience*, 14(11), 1475-1479.
- Shipp, S., Adams, R., A., & Friston, K. (2013). Reflections on agranular architecture: Predictive coding in the motor cortex. *Trends in Neurosciences*, 36(12), 706-716.
- Siegel, E. H., & Stefanucci, J. K. (2011). A little bit louder now: Negative affect increases perceived loudness. *Emotion*, 11(4), 1006.
- Singer, N., Eapen, M., Grillon, C., Ungerleider, L. G., & Hendler, T. (2012). Through the eyes of anxiety: Dissecting threat bias via emotional-binocular rivalry. *Emotion*, 12(5), 960.
- Solway, A., & Botvinick, M. M. (2012). Goal-directed decision making as probabilistic inference: A computational framework and potential neural correlates. *Psychological Review*, 119(1), 120.
- Spotorno, N., Cheylus, A., Van Der Henst, J., & Noveck, I. A. (2013). What's behind a P600? integration operations during irony processing. *PLOS ONE*, 8(6), e66839.
- Tajfel, H. (1982). Social psychology of intergroup relations. *Annual Review of Psychology*, 33(1), 1-39.
- Tong, F., Meng, M., & Blake, R. (2006). Neural bases of binocular rivalry. *Trends in Cognitive Sciences*, 10(11), 502-511.
- Unkelbach, C., Forgas, J. P., & Denson, T. F. (2008). The turban effect: The influence of muslim headgear and induced affect on aggressive responses in the shooter bias paradigm. *Journal of Experimental Social Psychology*, 44(5), 1409-1413.
- Van de Cruys, S., Evers, K., Van der Hallen, R., Van Eylen, L., Boets, B., de-Wit, L., & Wagemans, J. (2014). Precise minds in uncertain worlds: Predictive coding in autism. *Psychological Review*, 121(4), 649.

- Van Essen, D. C., Anderson, C. H., & Felleman, D. J. (1992). Information processing in the primate visual system: An integrated systems perspective. *Science (New York, N.Y.)*, 255(5043), 419-423.
- Vetter, P., & Newen, A. (2014). Varieties of cognitive penetration in visual perception. *Consciousness and Cognition*, 27, 62-75.
- von Helmholtz, H. (2005). *Treatise on physiological optics* Courier Corporation.
- Vuilleumier, P., & Pourtois, G. (2007). Distributed and interactive brain mechanisms during emotion face perception: Evidence from functional neuroimaging. *Neuropsychologia*, 45(1), 174-194.
- Watson, T. L., & Clifford, C. W. (2003). Pulling faces: An investigation of the face-distortion aftereffect. *Perception-London*, 32(9), 1109-1116.
- Wieser, M. J., Gerdes, A. B., Büngel, I., Schwarz, K. A., Mühlberger, A., & Pauli, P. (2014). Not so harmless anymore: How context impacts the perception and electrocortical processing of neutral faces. *NeuroImage*, 92, 74-82.
- Williams, D. R., & Rucker, T. D. (2000). Understanding and addressing racial disparities in health care. *Health Care Financing Review*, 21(4), 75-90.
- Wood, R. G., Corcoran, M. E., & Courant, P. N. (1993). Pay differences among the highly paid: The male-female earnings gap in lawyers' salaries. *Journal of Labor Economics*, , 417-441.
- Yuille, A., & Kersten, D. (2006). Vision as bayesian inference: Analysis by synthesis? *Trends in Cognitive Sciences*, 10(7), 301-308.
- Zeki, S., Watson, J. D., Lueck, C. J., Friston, K. J., Kennard, C., & Frackowiak, R. S. (1991). A direct demonstration of functional specialization in human visual cortex. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, 11(3), 641-649.

Ziegert, J. C., & Hanges, P. J. (2005). Employment discrimination: The role of implicit attitudes, motivation, and a climate for racial bias. *Journal of Applied Psychology, 90*(3), 553.